



(briefing)

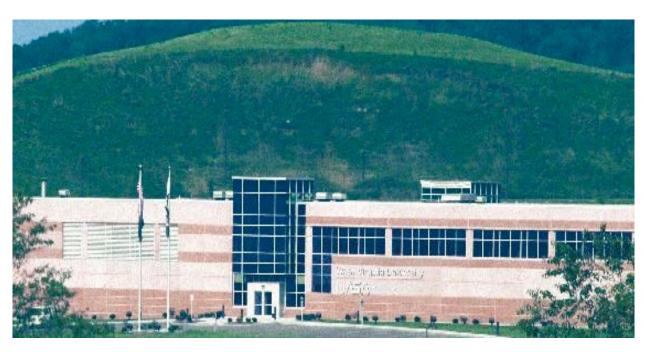


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Problem





Mountains of data

- Seek "the diamonds in the dust"
- We have many do-ings
 - But what are we learn-ing?
- What general lessons about software quality assurance can we offer NASA?
- Problem of external validity
 - It worked "there" but will it work "here"?



Approach



while not ((end of time OR end of money))

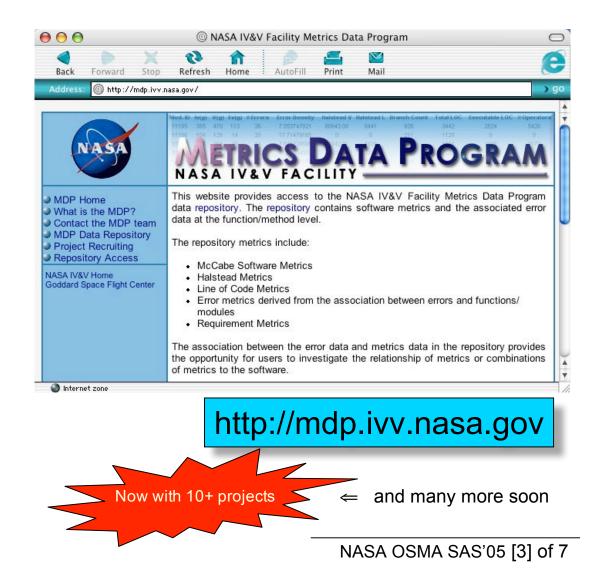
- chase data sets
- extract cost-benefit patterns from data
- check the stability of those patterns
- report stable conclusions

Product metrics:

- NASA metric's data program
- Goddard project
- Flight simulators

Process metrics:

- cost estimation data from JPL
 - Now spun off into a project with Jairus Hihn
- SILAP (IV&V effort potential model)





Importance/ Benefits





•Generally:

- -NASA does a lot of software
- -What guidance should we offer developers?
- –How good is that guidance
 - Has that guidance been certified?
 - Do we know how general are those guidelines?



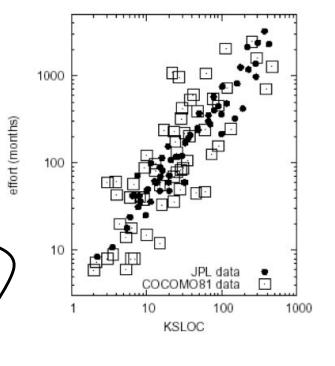
Relevance To NASA



Data comes from NASA

- Process metrics:
 - JPL project data
 - IV&V effort potential data
- Product metrics
 - Defect logs from multiple NASA centers
 - Flight simulator data

Conclusions apply to NASA projects



1	#	% with		developed	
project	modules	defects	language	at	notes
CM1	496	9.7%	С	location 2	a NASA spacecraft instrument
JM1	10885	19%	С	location 3	real-time predictive ground system: uses simulations to generate the predictions
KC1	2107	15.4%	C++	location 4	storage management for receiving and processing ground data
KC2	523	20%	C++	location 4	science data processing; another part of the same project as KC1; different per- sonnel to KC1. shared some third-party software libraries as KC1, but no other software overlap.
PC1	1107	6.8	C	location 5	support tools
Total	15118				•

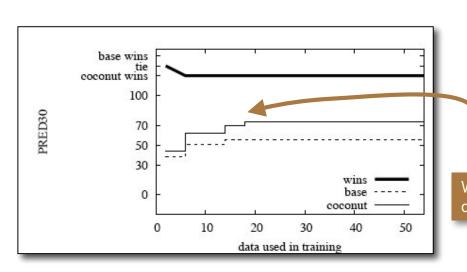
Accomplishments

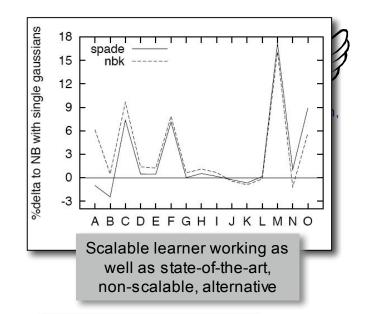
Before:

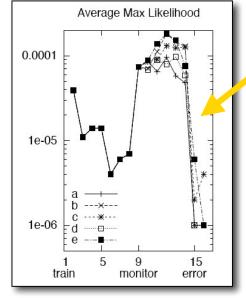
- —Can automatically learn defect detectors from error logs.
- Those defect detectors from code are much BETTER than previously believed
 - Yes, false negative, but adequate to good detection probabilities
 - (Enough) stability across multiple projects

• Now:

- Can automatically learn software cost models
 - AND determine how much data is required to do that
- -Can scale up to HUGE data sets
- -Can determine when a learned theory goes "out of scope"
- -See also "SPOT/CUBE" in "martha"







Where a learner has left the zone where it was certified

When we have seen enough data to learn a good cost model



Next Steps





- Got data?
 - Then meet your new best friend

Current plans

- More defect data studies
 - Dozens, not just 5, data sets
 - Check effectiveness and stability?
- Release of the generalized toolkits
 - Tutorials
 - manuals
- Generalized anomaly detectors
 - The "selection bias" problem
- Synergies with other SARP data mining projects

